FUTURE TECHNO SCIENCE

Journal of Future Artificial Intelligence and Technologies

E-ISSN: 3048-3719

Research Article

AI-Driven Hybrid Recommender Framework for Personalized Course Selection in Learning Platforms

Rashmi P. Bijwe * and **Anjali B. Raut**

Department of Computer Science & Engineering, H.V.P.M's College of Engineering & Technology, Hanuman Vyayam Nagar, Amravati, Maharashtra 444605, India;
e-mail : rashmi.bijwe100@gmail.com; dahakeanjali@gmail.com
* Corresponding Author : Rashmi P. Bijwe

Abstract: The rapid expansion of digital learning platforms has resulted in an overwhelming number of online courses, making it increasingly difficult for learners to identify offerings that align with their academic goals, skills, and interests. This study addresses this challenge by proposing a machine learning–based hybrid course recommendation framework that integrates content-based filtering and collaborative filtering to enhance personalized learning support. The proposed approach combines statistical and semantic text representations using Term Frequency–Inverse Document Frequency (TF–IDF) and Sentence-BERT (SBERT) embeddings, together with regression-based predictive modeling for learner preference estimation. Content-based filtering captures semantic similarity between learner profiles and course descriptions, while collaborative filtering predicts course ratings based on historical learner–course interactions, enabling a balanced and context-aware recommendation process. The framework is evaluated using two independent datasets: a large-scale public Coursera dataset for benchmarking and a real-time institutional dataset collected from engineering colleges in Maharashtra for practical validation. Experimental results indicate that models leveraging SBERT embeddings consistently outperform TF–IDF-based representations across multiple regression models, with the SBERT-Gradient Boosting Regressor combination achieving the most reliable performance in terms of Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2. These findings suggest that integrating semantic representations with predictive modeling improves recommendation accuracy and robustness across heterogeneous educational contexts. While a graphical user interface is presented to demonstrate real-world applicability, the primary contribution of this work lies in the methodological framework and its empirical validation. Overall, the proposed hybrid recommender framework offers a scalable and interpretable solution for personalized course selection and supports flexible, interdisciplinary learning objectives aligned with India's National Education Policy (NEP) 2020.

Keywords: Collaborative Filtering; Course Recommendation System; Hybrid Recommender System; Machine Learning; Personalized Learning; Sentence-BERT; Semantic Similarity; Educational Data Mining.

Received: December, 1st 2025
Revised: January, 28th 2026
Accepted: January, 29th 2026
Published: February, 12th 2026
Curr. Ver.: February, 12th 2026

1. Introduction

The rapid growth of digital education platforms and the increasing accessibility of online learning resources have fundamentally transformed how learners' access and interact with educational content. Massive Open Online Courses (MOOCs) and institutional e-learning platforms now offer thousands of courses across diverse domains. While this abundance of content offers flexibility and opportunities, it also poses a significant challenge: learners often struggle to identify courses that best align with their academic goals, skill levels, and personal interests. As a result, personalized course recommendation systems have become an essential solution for mitigating information overload by delivering adaptive, data-driven learning suggestions tailored to individual learners [1]–[4].

Traditional course recommendation approaches primarily rely on either content-based filtering (CBF) or collaborative filtering (CF). However, these methods often suffer from limitations such as data sparsity, cold-start problems, and inadequate handling of contextual variability. With recent advances in machine learning (ML) and natural language processing (NLP), hybrid recommender systems that integrate semantic understanding with predictive modeling have emerged as a promising alternative, offering improved accuracy and personalization [5]–[8]. Motivated by these developments, this study proposes an ML–based course recommendation framework that combines semantic representations derived from Sentence-BERT (SBERT) with regression-based CF models to generate context-aware, learner-specific course recommendations. The proposed system aims to support students and higher education institutions in improving the quality of course selection, promoting interdisciplinary learning, and facilitating open elective choices, in alignment with India's National Education Policy (NEP) 2020.

Although a growing body of research addresses course recommendation and retrieval-augmented learning systems, existing studies typically focus on either retrieval mechanisms or predictive model architectures in isolation. Consequently, limited attention has been given to the interaction between semantic feature representation and collaborative model design, particularly regarding how these components jointly influence recommendation performance, robustness, and generalization across diverse educational datasets. This lack of holistic analysis prevents a deeper understanding of how to optimize embedding strategies, feature representations, and predictive architectures together within hybrid recommender systems.

To address this gap, the present study introduces a hybrid course recommendation framework that explicitly integrates CBF and CF, demonstrating how semantic retrieval and predictive modeling architectures interact to enhance recommendation effectiveness. The framework incorporates two feature extraction techniques—TF-IDF and SBERT (SBERT)—to capture both statistical and deep semantic relationships within course descriptions, enabling a systematic comparison of their impact on predictive performance. Multiple regression models are employed for CF and learner rating prediction, illustrating how architectural choices complement semantic representations to improve personalization. The proposed approach is validated using two independent datasets: a benchmark Coursera dataset and a real-time institutional dataset collected from engineering colleges in Maharashtra. This dual-dataset evaluation demonstrates the robustness, generalization capability, and practical applicability of the framework. In addition, a lightweight graphical user interface (GUI) is provided to illustrate real-world deployment, allowing learners to receive personalized course recommendations based on their academic profiles and interests. Overall, this work contributes theoretical insights into hybrid recommender design while offering practical relevance for intelligent learning systems aligned with NEP 2020 objectives.

The remainder of this paper is organized as follows. Section 2 reviews related work on ML–based and hybrid recommender systems in e-learning environments. Section 3 presents the proposed methodology, including data preprocessing, feature extraction, and system architecture. Section 4 describes the experimental setup, datasets, evaluation metrics, and performance analysis. Finally, Section 5 concludes the paper and outlines potential directions for future research.

2. Related Work

A substantial body of research has investigated course recommendation systems in e-learning environments, primarily leveraging ML, deep learning (DL), and artificial intelligence (AI) techniques to enhance personalization and learning effectiveness. Early studies focused on utilizing learner feedback, ratings, and academic performance indicators to generate personalized course recommendations aligned with students' interests and goals [9]–[11]. These approaches demonstrated the potential of ML-driven recommender systems to support adaptive learning environments by analyzing historical educational data and learner behavior.

To further improve recommendation accuracy and adaptability, several works introduced hybrid recommendation strategies that combine CBF and CF. Genetic optimization and multi-criteria decision-making techniques were applied to balance learner interests, prerequisites, and performance variables for elective course selection [12]. Other frameworks integrated user behavior analysis, semantic similarity measures, and performance monitoring to enhance the relevance of recommendations and learner engagement [13]–[15]. Methods such as k-nearest neighbors, cumulative preference modeling, and implicit feedback mechanisms have also been explored to refine similarity assessment and recommendation quality in higher education settings [14], [16]–[19].

With the increasing availability of large-scale educational data, recent studies have incorporated DL models to capture complex learner–course relationships. Deep neural networks, contextual user profiling, and behavior-aware architectures have been proposed to support personalized learning resource recommendation and adaptive course selection in both institutional e-learning platforms and MOOCs [20]–[27]. Knowledge graphs and context-aware similarity measures have further been employed to enhance semantic understanding and recommendation precision, enabling systems to account for learner context, motivation, and engagement dynamics [28], [29].

Collaborative filtering–based approaches remain a central component of educational recommender systems, with extensions that incorporate contextual similarity, reinforcement learning, federated learning, and privacy-aware mechanisms to address heterogeneity and data sparsity across institutions [30]–[35]. Hybrid models combining CF and CBF have been shown to improve recommendation robustness and contextual relevance, particularly when integrated with explainable models, ensemble learning strategies, or multi-agent frameworks [36]–[40]. More recent works have explored semantic-rich representations and explainable architectures, including knowledge graph–based recommenders and Bayesian network models, to enhance transparency and interpretability in course and program recommendations [41]–[44].

Despite these advances, existing studies predominantly examine either retrieval-oriented semantic modeling or predictive architectural design in isolation. Many systems rely on shallow textual representations or simple statistical features, limiting their ability to capture deeper semantic relationships within course descriptions and learner preferences. Conversely, predictive models are often evaluated without a systematic analysis of how feature representation choices influence CF performance, generalization, and scalability across heterogeneous educational datasets. As a result, there remains a limited understanding of the joint impact of semantic embedding strategies and regression-based predictive architectures within hybrid recommender systems.

Addressing this gap, the present study proposes a hybrid course recommendation framework that explicitly integrates semantic feature extraction using TF-IDF and SBERT with regression-based CF models. By systematically analyzing how retrieval design and predictive architecture interact, and by validating the framework across both a benchmark MOOC dataset and a real-world institutional dataset, this work advances the state of the art in personalized educational recommender systems. The proposed approach emphasizes robustness, generalization, and practical applicability while aligning with contemporary educational objectives such as those outlined in NEP 2020.

3. Material and Method

The proposed ML–based recommender system is designed to deliver personalized course and open elective recommendations by integrating CBF and CF within a unified hybrid framework. As illustrated in Figure 1, the framework presents a generic methodological pipeline that is applied independently to each dataset. All preprocessing, feature extraction, model training, validation, and evaluation are performed separately for each dataset, and no data merging or cross-dataset information sharing occurs at any stage of the process. This design ensures methodological clarity, prevents data leakage, and enables independent validation of the proposed approach across heterogeneous educational contexts.

3.1. Student/Course Database

The Student/Course Database serves as the primary data repository for the recommender system and comprises two distinct datasets that represent complementary educational contexts. The use of two datasets is intentional: the Coursera dataset is employed to support large-scale validation and reproducibility, while the institutional dataset is used to assess real-world applicability within a formal academic environment. This dual-dataset strategy enables both robustness verification and contextual validation of the proposed methodology.

3.1.1. Coursera Dataset

The proposed system is evaluated using benchmark course data obtained from the Coursera platform [27], [45], a widely used web-based learning environment offering a diverse range of online courses. The dataset consists of 1,246 course samples, providing sufficient coverage for evaluating content-based similarity and recommendation strategies at scale. Given the extensive availability of both free and paid courses, learners often struggle to identify suitable courses aligned with their skill levels and learning objectives. This dataset enables the development of recommendation systems that leverage learners' capabilities and perceived difficulty levels to suggest appropriate courses. Each course entry contains structured metadata, including course descriptions, difficulty levels, and associated skill tags extracted using NLP techniques. A summary of the course attributes used in this study is provided in Table 1.

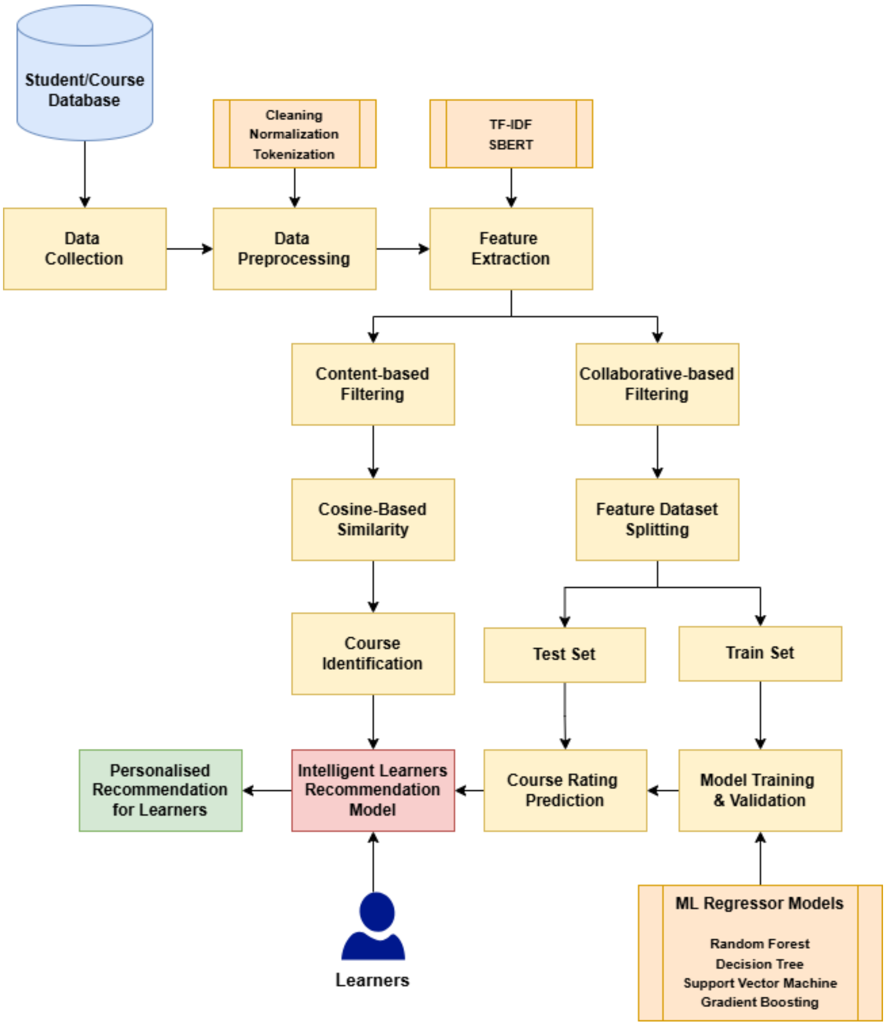

Figure 1. Recommender system framework for learners.

Table 1. Course details and attributes (Coursera dataset)

Entity	Attributes
Course Name	Name of the course
Difficulty Level	Beginner, Intermediate, Advanced
URL	Course access link
Course Description	Textual description of course content
University	Offering an institution or industry partner
Skills	Skill tags extracted via NLP
Course Rating	Rating on a 5-point scale (0.1 granularity)

3.1.2. Institutional Open Elective and Course Recommendation Dataset

In addition to the public benchmark dataset, a real-world institutional dataset was collected from several established engineering and technology colleges in Maharashtra, India. This dataset includes academic records for approximately 1,000 undergraduate students spanning semesters III to VII in the Information Technology (IT) discipline. The student data capture academic performance indicators such as completed courses, grades, and proficiency levels, along with contextual attributes including skills, learning preferences, and career objectives.

To support elective course recommendations, an additional course repository was constructed using data from NPTEL (National Programme on Technology Enhanced Learning), which provides a comprehensive collection of engineering courses with detailed descriptions, prerequisite information, subject domains, and difficulty levels. Student profiles and course profiles were systematically curated to enable effective matching between learner attributes and course characteristics.

Table 2. Student and Course Data Attributes (Institutional Dataset)

Entity	Attributes
Student Data	Timestamp, Enrollment ID, Gender (M/F), Region (District), Skills, Career Objective, Device Used (Mobile/Laptop), Previously Attended Courses
Course Data	Open Elective, Course Title, Instructor, Institution, Focus Summary, Prerequisites, Course Rating

All institutional and learner-related data were fully anonymized prior to analysis. Data collection and processing were conducted exclusively for academic research purposes and adhered to institutional guidelines and ethical research standards. No personally identifiable information or sensitive individual-level attributes were retained or utilized during the modeling process. A summary of the student and course attributes used in the institutional dataset is presented in Table 2.

3.2. Data Preprocessing

At this stage, the collected data undergo a systematic preprocessing pipeline designed to ensure data consistency, quality, and readiness for subsequent modeling tasks. The preprocessing steps include data cleaning, normalization, tokenization, stop-word removal, lemmatization, handling missing values, and feature integration. Let the raw dataset be denoted as:

$$D = \{d_1, d_2, \dots, d_n\} \tag{1}$$

where each record d_i represents either learner-related or course-related information. Data cleaning is first applied to remove duplicate, incomplete, and irrelevant records, resulting in a refined dataset $D \subset D$, defined as:

$$D' = \{d_i \in D | valid(d_i) = 1\} \tag{2}$$

where $valid(d_i)$ indicates that the record satisfies predefined quality criteria, including non-null values and contextual relevance.

Normalization is then performed to standardize numerical attributes and reduce scale-related biases. For a given numerical feature x, standard score normalization is applied as:

$$x' = \frac{x - \mu}{\sigma} \tag{3}$$

where μ and σ represent the mean and standard deviation of the feature, respectively. This ensures uniform scaling across different attributes.

Text normalization is applied in parallel, converting all textual content to lowercase and removing punctuation, digits, and special characters using regular expression–based processing through Python libraries such as re and string. Tokenization decomposes textual fields into individual word units:

$$T = \{t_1, t_2, \dots, t_m\} = tokenize(S) \tag{4}$$

where S denotes a textual field such as a course description, and t_i represents each tokenized word. NLP tools such as NLTK and SpaCy are employed for tokenization, stop-word removal, and lemmatization. Stop-word removal eliminates high-frequency, low-information terms, while lemmatization reduces words to their canonical base forms, thereby improving model generalization.

To address incomplete metadata, missing values are handled using appropriate imputation strategies, such as placeholder values (e.g., "N/A") or statistical imputation (e.g., mean imputation), implemented using pandas and scikit-learn utilities. Subsequently, multiple textual attributes—such as course title, description, and skill tags—are concatenated into a single unified textual representation:

$$C_i = concat(title_i, description_i, tags_i) \tag{5}$$

where C_i represents the final combined textual feature for course i.

This comprehensive preprocessing pipeline, implemented using Python libraries such as NLTK, SpaCy, pandas, NumPy, and scikit-learn, minimizes noise, enhances textual consistency, and ensures the processed dataset is optimally structured for accurate feature extraction and recommendation modeling [46].

3.3. Feature Extraction

This module transforms the preprocessed textual and numerical data into structured, machine-readable feature representations suitable for recommendation modeling. Two primary feature extraction techniques are employed: TF–IDF and SBERT.

3.3.1. Term Frequency–Inverse Document Frequency (TF–IDF)

TF–IDF is a statistical method used to quantify the importance of terms within a document relative to a corpus. It emphasizes terms that appear frequently in a particular document but are less common across the entire dataset. The term frequency (TF) of a term t in document d is defined as:

$$TF(t, d) = \frac{f_{t,d}}{\sum_k f_{k,d}} \tag{6}$$

where $f_{t,d}$ denotes the frequency of term t in document d, and the denominator represents the total number of terms in the document.

The inverse document frequency (IDF) measures the rarity of a term across the corpus:

$$IDF(t) = \log\left(\frac{N}{n_t}\right) \tag{7}$$

where N is the total number of documents and n_t is the number of documents containing the term t. The combined TF–IDF weight is computed as:

$$TF - IDF(t, d) = TF(t, d) \times IDF(t) \tag{8}$$

This formulation assigns lower weights to common but less informative terms (e.g., "course" or "learn") while emphasizing domain-specific and distinctive terms (e.g., "machine learning" or "data visualization"). In the proposed system, TF–IDF vectors represent the content features of courses and are later utilized in CBF. Cosine similarity is applied to these vectors to quantify textual similarity and support recommendation generation.

3.3.2. Sentence-BERT Embeddings

Sentence-BERT (SBERT) leverages transformer-based architectures to generate dense, contextualized vector representations that preserve semantic meaning beyond surface-level word frequencies. Each course description or learner profile is encoded into a semantic embedding vector:

$$v_i = f_{SBERT}(C_i) \tag{9}$$

where $f_{SBERT}(\cdot)$ denotes the SBERT embedding function applied to the combined textual representation C_i.

SBERT employs a bi-encoder architecture in which each sentence s is processed independently by a transformer model to produce an embedding:

$$v_s = f_{SBERT}(s) \tag{10}$$

In this study, embeddings are generated using the all-MiniLM-L6-v2 pretrained model, producing 768-dimensional vectors. Embeddings are normalized using min–max scaling to ensure compatibility across feature domains. These semantic representations support both content-based similarity computation and regression-based CF within the hybrid framework.

3.4. Content-Based Filtering

Content-based filtering (CBF) generates recommendations by matching learner preferences with course content characteristics. Using TF–IDF or SBERT feature representations, the system retrieves courses that are semantically and contextually aligned with a learner's profile or previously preferred courses. Similarity between courses is computed using cosine similarity:

$$\text{cosine\_sim}(A, B) = \frac{A \cdot B}{\|A\| \, \|B\|} \tag{11}$$

After computing similarity scores between the learner profile and all available courses, the system ranks the courses in descending order of similarity and selects the top candidates as recommendations. This process ensures that suggested courses closely align with learners' interests, educational objectives, and prior learning experiences, enhancing personalization and relevance within the hybrid recommender system.

3.5. Collaborative Filtering

The CF component focuses on predicting learners' course preferences by analyzing historical user–course interactions rather than relying solely on course metadata. Unlike CBF, this approach leverages patterns observed across multiple learners to infer preferences, thereby addressing sparsity and personalization limitations inherent in purely content-driven methods.

In the proposed framework, CF is implemented using regression-based ML models, including Decision Tree Regressor (DTR), Random Forest Regressor (RFR), Support Vector Regressor (SVR), and Gradient Boosting Regressor (GBR). These models are selected for their ability to capture both linear and nonlinear relationships between learner attributes, course features, and observed feedback. The target variable represents either explicit ratings provided by learners or inferred scores derived from academic performance indicators and interaction history. Formally, the predicted rating of user u for course i is expressed as:

$$\hat{r}_{u,i} = f(x_u, y_i; \theta) \tag{12}$$

where x_u and y_i denote the feature vectors of the learner and course, respectively, θ represents the learned model parameters, and $f(\cdot)$ corresponds to the regression function implemented by the selected ML model.

The predicted ratings generated by the CF models are subsequently integrated into the hybrid recommendation process. This enables the system to account not only for semantic similarity between courses but also for learner satisfaction and behavioral relevance, thereby improving overall recommendation accuracy and personalization.

3.6. Feature Dataset Splitting

After feature extraction and integration, the dataset is partitioned into training and testing subsets to ensure unbiased performance evaluation. The training set is used to learn the parameters of the CF regression models, allowing them to capture underlying rating patterns and relationships. The testing set is reserved exclusively for evaluation, assessing the models' ability to generalize to unseen learner–course pairs. In the proposed experiments, 80% of the data is allocated for training, while the remaining 20% is used for testing. These split balances learning efficiency and evaluation reliability, helping to mitigate overfitting and ensuring that reported results reflect true predictive performance.

3.7. Machine Learning Regressor Models

Several ML regression models are trained and evaluated to predict learner ratings for candidate courses. These models collectively form the predictive core of the CF module.

- DTR predicts continuous rating values by recursively partitioning the feature space into regions that minimize prediction error. Within the recommendation context, it models decision rules based on learner and course attributes, providing an interpretable baseline for rating prediction. The predicted value at a leaf node corresponds to the mean rating of samples assigned to that node, with splits determined by minimizing the mean squared error (MSE).
- RFR is an ensemble method that aggregates predictions from multiple decision trees trained on bootstrapped samples and randomly selected feature subsets. This ensemble strategy reduces variance and improves generalization compared to a single decision tree. The final predicted rating is computed as the average prediction across all trees:

$$\hat{r}(x) = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \tag{13}$$

  where T is the number of trees and $f_t(x)$ denotes the prediction of the t-th tree
- SVR estimates continuous outputs by fitting a function within a specified error tolerance ϵ, while maintaining model simplicity. By employing kernel functions such as linear or radial basis function (RBF), SVR effectively captures nonlinear relationships between learner–course features and predicted ratings. The model balances prediction accuracy and complexity through a regularization parameter C.
- GBR constructs an additive ensemble of weak learners in a stage-wise manner, where each successive model focuses on correcting the residual errors of its predecessors. The model is iteratively updated as:

$$F_m(x) = F_{m-1}(x) + \eta h_m(x) \tag{14}$$

  where $F_m(x)$ represents the model after the m-th iteration, $h_m(x)$ is the weak learner, and η is the learning rate. By minimizing a differentiable loss function, GBR achieves high predictive accuracy and robustness.

Each regression model is trained and evaluated using identical feature representations and evaluation protocols, enabling a fair comparison of their effectiveness in predicting learner ratings. The resulting predictions are subsequently combined with content-based similarity scores within the hybrid recommendation framework.

3.8. Intelligent Learners Recommendation Model

The Intelligent Learners Recommendation Model integrates the outputs of the CBF and CF components into a unified decision-making mechanism. Rather than relying on a single source of information, this model combines semantic similarity scores derived from content analysis with predicted learner ratings generated by regression-based CF models.

By jointly considering learner-specific preferences and collective behavioral patterns, the hybrid model produces more balanced and accurate recommendations. This integration enhances personalization while mitigating the limitations of standalone CBF or CF approaches, such as cold-start effects or sparse interaction data. The overall model construction and training workflow for both CBF and CF components is summarized in Algorithm 1.

3.9. Personalized Recommendation for Learners

In the final stage, the system generates a personalized list of recommended courses or open electives for each learner. Recommendations are ranked based on a unified score that reflects both content relevance and predicted learner satisfaction, ensuring alignment with individual educational objectives, prior learning behavior, and skill interests.

The final recommendation score for a course i is obtained by combining the normalized content similarity score from the SBERT-based content model with the predicted rating produced by the CF regressor. This hybrid scoring strategy yields a single, coherent recommendation that balances semantic relevance and behavioral evidence. The model-building and training process is formally described in Algorithm 1, while the user testing and recommendation-generation process is detailed in Algorithm 2.

Algorithm 1. Model Building Phase

INPUT: Preprocessed student and course datasets
OUTPUT: Trained CBF and CF models
1: Load the preprocessed student and course datasets.
2: Perform feature extraction using:
3: TF–IDF to generate term-weight vectors, or
4: SBERT to obtain semantic embeddings.
5: Implement CBF:
6: Compute cosine similarity between course features and learner profiles.
7: Construct the similarity matrix $S(i, j)$
8: Implement CF:
9: Prepare the learner–course interaction feature matrix.
10: Split the dataset into 80% training and 20% testing sets.
11: Train regression-based models (Decision Tree, Random Forest, Support Vector Regressor, and Gradient Boosting) to predict course ratings.
12: Evaluate trained models using performance metrics such as MAE, RMSE, and R^2
13: Save the best-performing model for deployment in the recommendation phase.

Algorithm 2. User Testing and Recommendation Phase

INPUT: Trained CBF and CF models, new learner profile
OUTPUT: Personalized course or elective recommendations
1: Accept learner profile or feedback data as input.
2: Preprocess the input data, including cleaning, tokenization, and embedding generation.
3: Apply the CBF module to compute content similarity scores for the learner.
4: Apply the CF module to predict personalized course ratings using the trained regression model.
5: Combine outputs from the CBF and CF modules to compute the final recommendation score $R(i)$
6: Rank courses based on $R(i)$
7: Display the top-N recommended courses or electives to the learner.

4. Experimental Results and Discussion

4.1. Experimental Setup

The proposed hybrid course recommendation system was implemented in Python using the PyCharm IDE within an Anaconda environment for dependency management and reproducibility. The system was trained and evaluated on both the Coursera dataset and the institutional open elective dataset to assess robustness and real-world applicability. All experiments were conducted on a Windows 11 workstation equipped with an Intel Core i5 processor, 16 GB RAM, and a 4 GB GPU, which provided sufficient computational capacity for training and evaluating high-dimensional text representations such as TF–IDF vectors and SBERT embeddings.

4.2. Performance Evaluation Measures

The performance of the proposed hybrid recommender system was evaluated using standard regression metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R^2). These metrics assess prediction accuracy, sensitivity to large errors, and explanatory power by comparing predicted ratings with actual learner ratings. The evaluation metrics are formally defined as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (15)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{17}$$

where N is the total number of observations, y_i denotes the actual rating value, $\hat{y}_i$ denotes the predicted rating value, and $\bar{y}$ is the mean of the actual ratings.

To ensure a robust and unbiased evaluation, 5-fold cross-validation was employed. In each iteration, four folds were used for training and one-fold for testing, following an 80:20 data split. This process was repeated 5 times, and the final results were reported as the mean $\pm$ standard deviation across all folds. This strategy minimizes data partition bias and provides a reliable estimate of model generalization performance.

Hyperparameter tuning was conducted using grid search for all regression models. The optimized configurations were: DTR (max depth = 10), RFR (100 estimators, max depth = 15), SVR (RBF kernel, C=1.0, gamma = 'scale'), and GBR (200 estimators, learning rate = 0.1, max depth = 5). These settings were applied consistently across datasets to ensure reproducibility.

4.3. Result Evaluation on the Coursera Dataset

This subsection presents the experimental results obtained on the Coursera dataset. The evaluation consists of two complementary analyses: (i) qualitative assessment of content-based retrieval effectiveness and (ii) quantitative evaluation of rating prediction accuracy using regression-based collaborative filtering.

```
Course Name:  Python Programming Essentials
Courses to recommend to user:
-----------------------------------------------------------------
Python Data Representations
Python Data Analysis
Python Basics
Programming for Everybody (Getting Started with Python)
Python Functions Files and Dictionaries
-----------------------------------------------------------------
```

Figure 2. Test case illustrating top-N course recommendations for a selected query course.

Figure 2 illustrates a representative test case in which a selected course title is used as a query, and the system retrieves the top five recommended courses $(N = 5)$. The recommended courses exhibit strong semantic alignment with the input query, demonstrating the effectiveness of the content-based component in capturing contextual and conceptual similarities across course descriptions. This result highlights the system's ability to maintain retrieval relevance even as semantic diversity increases. For collaborative filtering, regression models were trained independently using TF–IDF and SBERT feature representations. Their performance was evaluated using MAE, MSE, and R^2 scores, with the results summarized in Table 3.

As shown in Table 3, ensemble-based models consistently outperform simpler regressors. In particular, the GBR combined with SBERT features achieves the best overall performance, with the lowest MSE (0.0278), lowest MAE (0.1269), and highest R^2 score (0.8896). The RFR with SBERT embeddings also demonstrates strong predictive capability, achieving an R^2 score of 0.8715, indicating its effectiveness in modeling nonlinear learner–course relationships. The comparative performance trends are shown in Figure 3, further confirming the superiority of SBERT-based representations across all evaluated regression models.

Table 3. Performance comparison of regression models using TF–IDF and SBERT features on the Coursera dataset.

Regressor Model	Feature Representation	MSE	MAE	R^2 Score
Decision Tree Regressor (DTR)	TF–IDF	0.0720	0.1998	0.7053
	SBERT	0.0612	0.1714	0.7428
Random Forest Regressor (RFR)	TF–IDF	0.0366	0.1493	0.1319
	SBERT	0.0297	0.1325	0.8715
Support Vector Regressor (SVR)	TF–IDF	0.0524	0.1766	0.2414
	SBERT	0.0431	0.1572	0.8023
Gradient Boosting Regressor (GBR)	TF–IDF	0.0425	0.1855	0.6731
	SBERT	0.0278	0.1269	0.8896

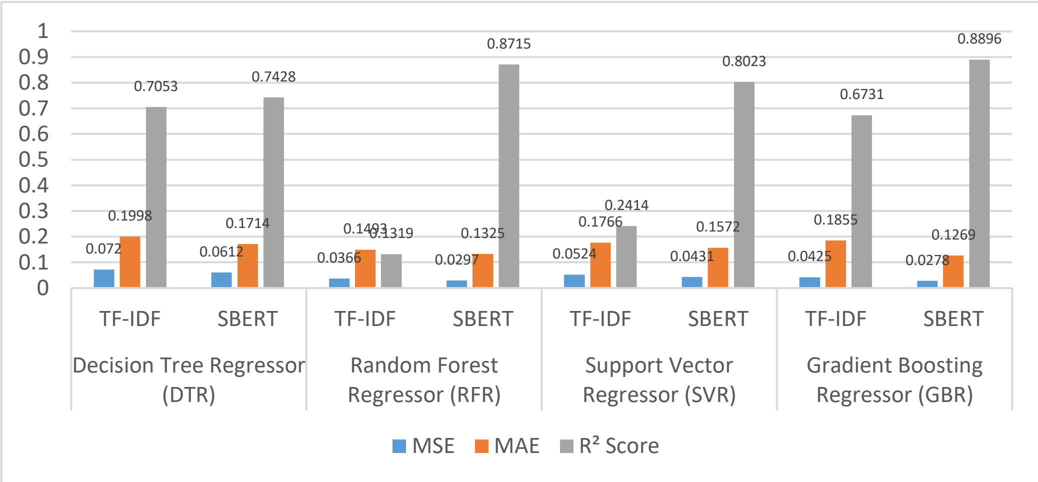

Figure 3. Comparative evaluation of regression models using TF–IDF and SBERT features.

Simpler models such as DTR and SVR exhibit moderate performance. While DTR benefits from SBERT features, it remains more susceptible to overfitting due to its single-tree structure. SVR achieves reasonable predictive accuracy with SBERT (R^2 = 0.8023), but requires careful hyperparameter tuning for optimal performance. Overall, these results demonstrate that semantic-rich SBERT embeddings, when combined with regression-based collaborative filtering, substantially improve prediction accuracy and explanatory power. The hybrid integration of content-based and collaborative signals enables the proposed system to deliver accurate and personalized course recommendations.

4.4. Result Evaluation on the Real-Time Open Elective/Course Dataset

This subsection presents the experimental evaluation of the proposed hybrid course recommendation framework using the real-time institutional dataset, with a focus on comparing TF–IDF and SBERT feature representations in a practical academic setting. The dataset was collected through a structured Google Form survey distributed among students from multiple reputed Colleges of Engineering and Technology in Maharashtra, with a particular focus on the Information Technology discipline.

The collected data were organized into two primary components: User Data and Course Data. The User Data include learner-specific attributes such as enrollment identifiers, demographic information, skills, career objectives, preferred learning devices, and previously attended courses. These attributes provide insight into individual learning preferences, technological access, and prior exposure to specific academic domains. The Course Data were compiled from the NPTEL repository and contain detailed metadata for engineering courses, including course titles, open elective classifications, instructors, offering institutions, domain emphasis, course overviews, and rating criteria. Together, these attributes support fine-grained alignment between learner profiles and course characteristics.

The dataset spans students from Semesters III to VII, enabling a longitudinal evaluation of recommendation performance across different stages of academic progression. By combining learner feedback with institutionally curated course information, the dataset reflects realistic learning behaviors and evolving academic goals. This structure provides a suitable basis for evaluating the proposed hybrid recommendation framework in terms of adaptability, contextual relevance, and personalization.

Figure 4 illustrates representative recommendation results for Semester III learners. The hybrid model generates open elective suggestions and associated course recommendations that align with learners' skills and academic objectives. These results qualitatively demonstrate how the integration of semantic content representations (TF–IDF/SBERT) with regression-based collaborative filtering supports more informed and context-aware elective selection. While this figure primarily serves an illustrative purpose, it provides concrete evidence of the system's practical applicability in supporting NEP-aligned, flexible learning pathways. The same processing pipeline and evaluation procedure were applied consistently to datasets from Semesters IV, V, VI, and VII. This uniform methodology ensures that observed performance trends across semesters reflect genuine model behavior rather than variations in preprocessing or experimental setup.

Figure 5 presents the graphical user interface developed to demonstrate the system's practical deployment. The interface allows learners to input their skills or career objectives and receive corresponding elective and course recommendations. As the primary contribution of this study lies in the recommendation methodology rather than the interface design, the GUI is presented solely to illustrate end-user interaction with the proposed hybrid model.

The quantitative evaluation focuses on the collaborative filtering component, where regression models are used to predict learner ratings across all semesters. Table 4 summarizes the performance of DTR, RFR, SVR, and GBR using TF–IDF and SBERT feature representations. Performance is reported using MAE, MSE, and R^2 metrics.

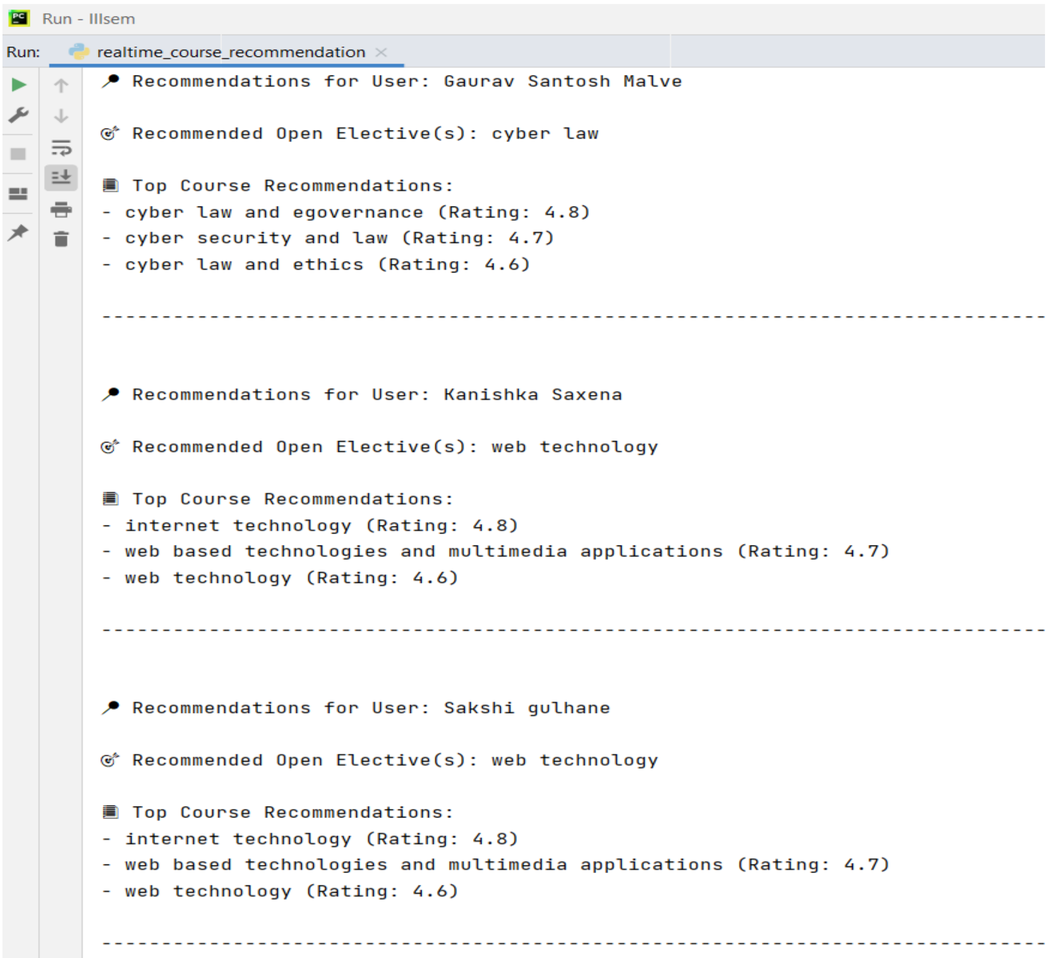

Figure 4. Recommended open electives and course suggestions for a Semester III learner.

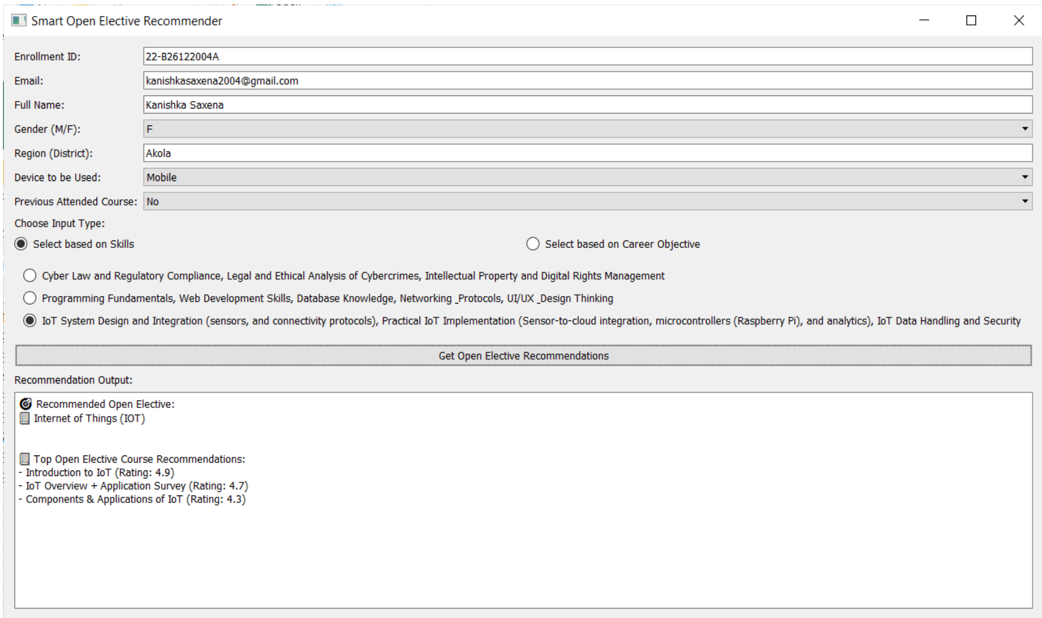

Figure 5. GUI-based open elective and course recommendations for a Semester III learner based on skill selection.

Table 4. Performance comparison of regression models using TF–IDF and SBERT features across all semesters (real-time institutional dataset)

Semester	Model	MAE (TF–IDF)	MAE (SBERT)	MSE (TF–IDF)	MSE (SBERT)	R^2 (TF–IDF)	R^2 (SBERT)
Sem-III	DTR	0.1333	0.1120	0.0266	0.0201	0.7500	0.8200
	RFR	0.1429	0.1080	0.0121	0.0098	0.6859	0.8320
	SVR	0.0889	0.0725	0.0087	0.0070	0.2042	0.5300
	GBR	0.0852	0.0658	0.0231	0.0174	0.7161	0.8500
Sem-IV	DTR	0.1333	0.1125	0.0200	0.0148	0.3440	0.5700
	RFR	0.1307	0.1050	0.0216	0.0161	0.2792	0.6150
	SVR	0.1463	0.1185	0.0840	0.0612	0.1350	0.4120
	GBR	0.1164	0.0935	0.0126	0.0095	0.3757	0.6420
Sem-V	DTR	0.1111	0.0910	0.0355	0.0251	0.2222	0.5250
	RFR	0.0950	0.0782	0.0979	0.0725	0.3596	0.5850
	SVR	0.0873	0.0715	0.0121	0.0095	0.3053	0.5400
	GBR	0.0861	0.0689	0.0126	0.0092	0.2953	0.5580
Sem-VI	DTR	0.1000	0.0820	0.0066	0.0048	0.6000	0.7950
	RFR	0.0973	0.0788	0.0192	0.0136	0.3895	0.6500
	SVR	0.1195	0.0972	0.0217	0.0170	0.6941	0.7950
	GBR	0.1106	0.0880	0.0155	0.0110	0.5720	0.7580
Sem-VII	DTR	0.1444	0.1200	0.0322	0.0246	0.2556	0.5100
	RFR	0.1266	0.1042	0.0236	0.0171	0.2758	0.5650
	SVR	0.2008	0.1625	0.0361	0.0224	0.1636	0.3850
	GBR	0.1365	0.1112	0.0246	0.0178	0.2612	0.5420

The results in Table 4 indicate a consistent performance advantage of SBERT-based representations over TF–IDF across all semesters and regression models. SBERT features generally yield lower MAE and MSE values, along with higher R^2 scores, suggesting improved predictive accuracy and stronger explanatory power. This trend is particularly evident for ensemble models such as GBR and RFR, which benefit from SBERT's ability to encode semantic and contextual information from course descriptions.

For instance, in Semester III, the GBR model achieves an MAE of 0.0658, an MSE of 0.0174, and an R^2 score of 0.85 using SBERT features, outperforming its TF–IDF counterpart across all metrics. Similar patterns are observed in subsequent semesters, indicating that the proposed hybrid framework maintains stable performance as learners progress through different stages of their academic programs. The comparative trends across all semesters are further illustrated in Figures 6–8, which present MAE, MSE, and R^2 evaluations, respectively.

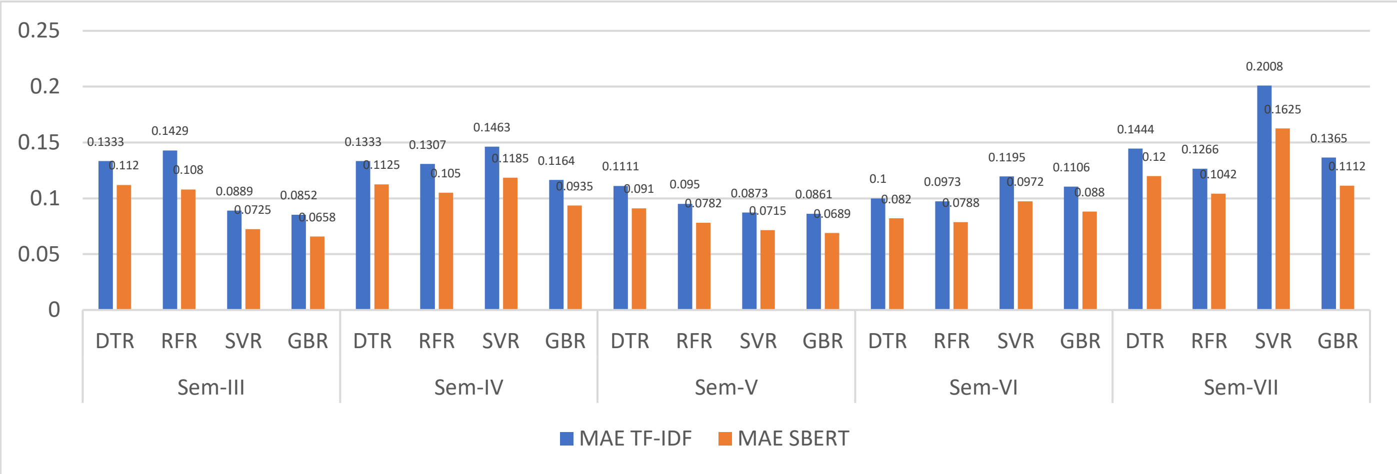

Figure 6. MAE comparison between TF–IDF and SBERT using regression models across semesters.

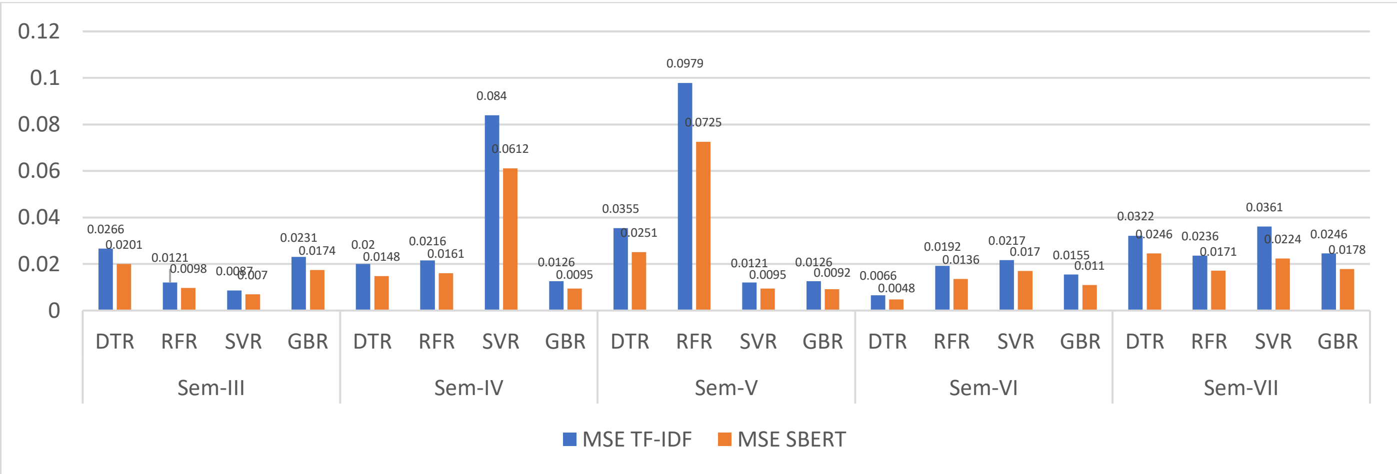

Figure 7. MSE comparison between TF–IDF and SBERT using regression models across semesters.

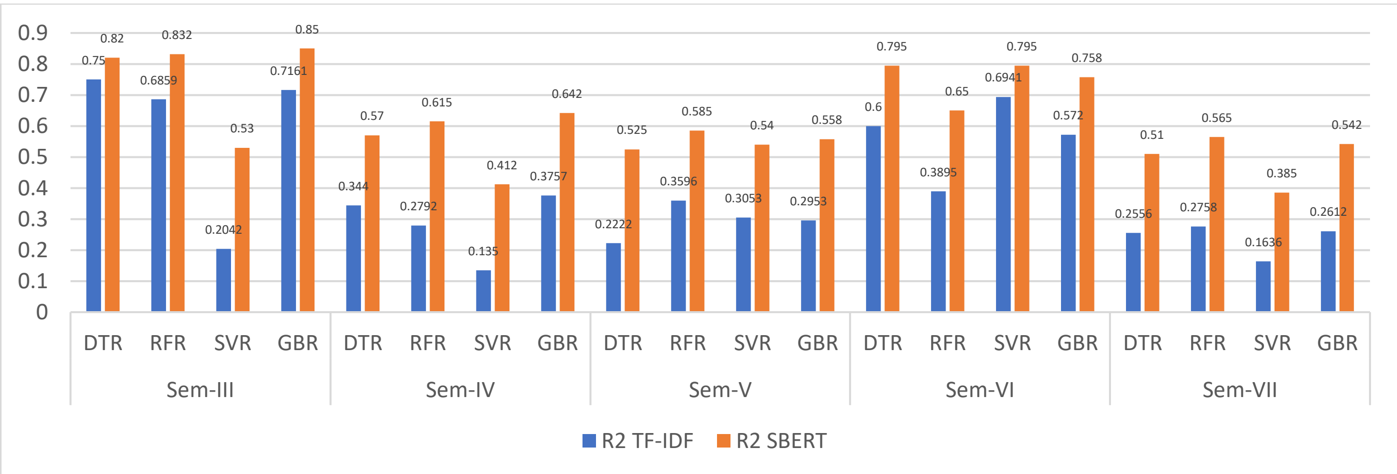

Figure 8. R^2 comparison between TF–IDF and SBERT using regression models across semesters.

4.5. Discussion

The experimental results obtained from the real-time institutional dataset demonstrate the effectiveness and adaptability of the proposed hybrid course recommendation framework. Across all evaluated semesters, models utilizing SBERT-based feature representations consistently outperform their TF–IDF counterparts, as evidenced by lower prediction errors and higher R^2 scores. This trend indicates that semantic-rich embeddings meaningfully improve the modeling of learner preferences in educational recommendation settings.

Among the evaluated regression models, the GBR and RFR exhibit the most reliable and stable performance. These ensemble methods are particularly effective at capturing complex, nonlinear relationships between learner profiles and course attributes. An R^2 value approaching 0.89 suggests that the proposed hybrid model explains a substantial proportion of the variance in learner rating behavior. From a practical perspective, this level of explanatory power implies more consistent and dependable course personalization, enabling learners to identify electives that are better aligned with their academic interests, skill development needs, and long-term educational objectives. Rather than merely improving numerical accuracy, such predictive reliability enhances learners' confidence in recommendation outcomes and supports more informed academic decision-making.

Importantly, consistent performance gains are observed across both the large-scale Coursera dataset and the institutional dataset. The repeated superiority of the SBERT + GBR combination across two heterogeneous datasets indicates that the proposed approach is not tailored to a single data source but instead demonstrates robustness across differing data distributions and educational contexts. This consistency supports the generalizability of the semantic–predictive integration strategy and suggests its suitability for deployment in real-world academic environments.

The observed performance improvements can be attributed to the complementary strengths of the two core components. SBERT provides deep contextual semantic representations that capture nuanced relationships within course descriptions and learner interests, while ensemble regression models such as GBR effectively model nonlinear preference patterns and interaction effects. Together, these components form a balanced hybrid framework that integrates semantic understanding with predictive modeling.

The inclusion of real-world institutional data, complemented by a GUI-based recommendation interface, further reinforces the practical relevance of the proposed system. While the graphical interface primarily serves as an illustrative deployment example rather than a core contribution, it demonstrates how the underlying recommendation model can support context-sensitive open elective selection aligned with learner competencies, career aspirations, and NEP 2020 guidelines.

Finally, the discussion of limitations highlights the interconnected nature of technical and ethical considerations in AI-driven educational recommendation systems. Limitations in semantic representation, retrieval accuracy, or predictive modeling can influence fairness, transparency, and user trust. Conversely, ethical requirements such as data privacy, anonymization, and bias mitigation impose constraints on model design and data utilization. Recognizing this interdependence underscores the need for a holistic approach that jointly addresses technical robustness and ethical responsibility. Although advanced semantic models increase computational complexity, the use of regression-based ensemble learners provides a degree of interpretability, helping balance predictive accuracy with explainability. This balance is essential for fostering trust and accountability in personalized learning environments.

5. Conclusions

This paper presented a hybrid machine learning–based course recommendation framework that aims to enhance personalized learning by integrating content-based and collaborative filtering techniques. The proposed approach combines TF–IDF and SBERT embeddings for semantic feature extraction with regression-based predictive modeling, including Decision Tree, Random Forest, Support Vector, and Gradient Boosting regressors, to generate context-aware course recommendations.

The framework was evaluated using two independent datasets: a public Coursera dataset and a real-time institutional dataset collected from engineering colleges in Maharashtra. Across both datasets, models leveraging SBERT-based semantic representations—particularly when combined with the Gradient Boosting Regressor—consistently achieved better performance on MAE, MSE, and R^2 metrics. These findings indicate that incorporating semantic similarity analysis alongside predictive modeling can improve rating prediction accuracy and support more effective personalization across heterogeneous educational data sources.

From a methodological perspective, the study demonstrates that integrating semantic embeddings with regression-based predictive models provides a coherent way to capture both contextual relationships in course content and nonlinear patterns in learner preferences. Rather than proposing a new architecture, the work offers empirical evidence that carefully combining established semantic representations with predictive learning techniques can yield robust performance within a unified recommendation framework. The comparative evaluation across two distinct datasets further suggests that the proposed approach is reasonably stable across different educational contexts. While a GUI-based implementation is included to illustrate real-time applicability, the primary contribution of this study lies in the methodological framework and its empirical validation. The proposed system supports interpretable, scalable recommendations and aligns with policy-driven educational objectives, such as those outlined in NEP 2020.

Despite these promising results, several limitations remain. The evaluation is limited to two datasets and a specific set of regression-oriented metrics (MAE, MSE, and R^2). Future studies could strengthen the generalizability of the findings by incorporating larger and more diverse datasets, additional recommendation-oriented evaluation metrics (e.g., Precision@K, Recall@K, NDCG, and user satisfaction measures), and longitudinal user studies to assess real-world impact over time.

Future work may also explore integrating adaptive learning mechanisms, such as deep learning or reinforcement learning, to enable recommendations that dynamically respond to evolving learner behavior. Incorporating multimodal data sources—including learner interaction logs, engagement patterns, and instructional media—could further enrich personalization. In addition, deploying the framework using scalable architectures, such as cloud-based or federated learning environments, may enhance scalability and privacy preservation, while tighter integration with institutional learning management systems could support real-time feedback, adaptive assessment, and intelligent academic support. These extensions would further strengthen the practical relevance of the proposed framework and support the development of data-driven digital education ecosystems aligned with the objectives of NEP 2020.

Author Contributions: Conceptualization: R.P.B. and A.B.R.; Methodology: R.P.B.; Software: R.P.B.; Validation: R.P.B. and A.B.R.; Formal analysis: R.P.B.; Investigation: R.P.B.; Resources: A.B.R.; Data curation: R.P.B.; Writing—original draft preparation: R.P.B.; Writing—review and editing: A.B.R.; Visualization: R.P.B.; Supervision: A.B.R.; Project administration: A.B.R.; Funding acquisition: A.B.R. All authors have read and agreed to the published version of the manuscript.

Funding:: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] S. Gheewala, S. Xu, and S. Yeom, "In-depth survey: deep learning in recommender systems—exploring prediction and ranking models, datasets, feature analysis, and emerging trends," *Neural Comput. Appl.*, vol. 37, no. 17, pp. 10875–10947, Jun. 2025, doi: 10.1007/s00521-024-10866-z.

[2] D. G. M., R. H. Goudar, A. A. Kulkarni, V. N. Rathod, and G. S. Hukkeri, "A Digital Recommendation System for Personalized Learning to Enhance Online Education: A Review," *IEEE Access*, vol. 12, pp. 34019–34041, 2024, doi: 10.1109/ACCESS.2024.3369901.

[3] D. Poornima and D. Karthika, "E-Learning Recommendation System and Classification Techniques - A Survey," *Nat. Compano*, vol. 28, no. 1, pp. 2893–2902, 2024, [Online]. Available: https://museonaturalistico.it/index.php/journal/article/view/556

[4] A. Narimani and E. Barberà, "Extracting Course Features and Learner Profiling for Course Recommendation Systems: A Comprehensive Literature Review," *Int. Rev. Res. Open Distrib. Learn.*, vol. 25, no. 1, pp. 197–225, Mar. 2024, doi: 10.19173/irrodl.v25i1.7419.

[5] M. T. Sharad Phalle and P. S. Bhushan, "Content Based Filtering And Collaborative Filtering: A Comparative Study," *J. Adv. Zool.*, vol. 45, no. s4, pp. 96–100, Mar. 2024, doi: 10.53555/jaz.v45iS4.4158.

[6] F. L. da Silva, B. K. Slodkowski, K. K. A. da Silva, and S. C. Cazella, "A systematic literature review on educational recommender systems for teaching and learning: research trends, limitations and opportunities," *Educ. Inf. Technol.*, vol. 28, no. 3, pp. 3289–3328, Mar. 2023, doi: 10.1007/s10639-022-11341-9.

[7] C. Lahoud, S. Moussa, C. Obeid, H. El Khoury, and P.-A. Champin, "A comparative analysis of different recommender systems for university major and career domain guidance," *Educ. Inf. Technol.*, vol. 28, no. 7, pp. 8733–8759, Jul. 2023, doi: 10.1007/s10639-022-11541-3.

[8] S. S. Khanal, P. W. C. Prasad, A. Alsadoon, and A. Maag, "A systematic review: machine learning based recommendation systems for e-learning," *Educ. Inf. Technol.*, vol. 25, no. 4, pp. 2635–2664, Jul. 2020, doi: 10.1007/s10639-019-10063-9.

[9] J. T. Iorzua, T. Moses, C. I. Eke, O. J. Agushaka, D. K. Kwaghtyo, and T. Godswill, "A Machine Learning Based Approach to Course and Career Recommendation System: A Systematic Literature Review," *J. Comput. Theor. Appl.*, vol. 3, no. 1, pp. 1–16, Jun. 2025, doi: 10.62411/jcta.12603.

[10] N. Pal, O. Dahiya, and M. Rana, "Advancing Educational Recommender Systems: An AI-Based Model for Personalized Learning Resource Recommendation," *Int. J. Eng. Trends Technol.*, vol. 73, no. 5, pp. 304–327, May 2025, doi: 10.14445/22315381/IJETT-V73I5P126.

[11] Meenakshi, G. Murugesan, J. T. Minoza, R. C. Panzo, L. B. Peconcillo, and D. T. Sanchez, "Machine learning in education for real time course recommendation system," in *AIP Conf. Proc. 3306*, 2025, p. 050015. doi: 10.1063/5.0275828.

[12] A. Esteban, A. Zafra, and C. Romero, "Helping university students to choose elective courses by using a hybrid multi-criteria recommendation system with genetic optimization," *Knowledge-Based Syst.*, vol. 194, p. 105385, Apr. 2020, doi: 10.1016/j.knosys.2019.105385.

[13] W.-E. Kong, S.-C. Haw, N. Palanichamy, and S. H. A. Rahman, "An e-Learning Recommendation System Framework," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 14, no. 1, pp. 10–19, Feb. 2024, doi: 10.18517/ijaseit.14.1.19043.

[14] G. George and A. M. Lal, "PERKC: Personalized kNN With CPT for Course Recommendations in Higher Education," *IEEE Trans. Learn. Technol.*, vol. 17, pp. 885–892, 2024, doi: 10.1109/TLT.2023.3346645.

[15] H. Xu, B. Hu, X. Gu, and L. Zheng, "A Learning Resource Recommendation Algorithm Based on Online Learning Behavior," in *ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Apr. 2024, pp. 5870–5874. doi: 10.1109/ICASSP48485.2024.10445936.

[16] M. Mouhiha, O. A. Oualhaj, and A. Mabrouk, "Combining Collaborative Filtering and Content Based Filtering for Recommendation Systems," in *2024 11th International Conference on Wireless Networks and Mobile Communications (WINCOM)*, Jul. 2024, pp. 1–6. doi: 10.1109/WINCOM62286.2024.10658169.

[17] J. Alanya-Beltran, "Personalized Learning Recommendation System in E-learning Platforms Using Collaborative Filtering and Machine Learning," in *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, May 2024, pp. 1–5. doi: 10.1109/ACCAI61061.2024.10602322.

[18] K. Thammarak, W. Kesornsit, and Y. Sirisathitkul, "Predictive Model for Academic Training CourseRecommendations Based on Machine LearningAlgorithms," *Int. J. Mod. Educ. Comput. Sci.*, vol. 16, no. 3, pp. 17–26, Jun. 2024, doi: 10.5815/ijmecs.2024.03.02.

[19] S. M. K. H. Nurakhmadyavi and E. E. Wahyudi, "Course Recommendation on Online Learning Platforms using Collaborative Filtering and Content-based Filtering with Implicit Feedback," in *2024 2nd International Conference on Software Engineering and Information Technology (ICoSEIT)*, Feb. 2024, pp. 25–30. doi: 10.1109/ICoSEIT60086.2024.10497495.

[20] T. C. Uzoma, C. O. Ikerionwu, M. E. Nwanga, and C. Etus, "Machine Learning Recommender System for an Enhanced Students Course Selection," *Int. J. Comput. Trends Technol.*, vol. 72, no. 10, pp. 31–35, Oct. 2024, doi: 10.14445/22312803/IJCTT-V72I10P106.

[21] S. Amin, M. I. Uddin, A. A. Alarood, W. K. Mashwani, A. O. Alzahrani, and H. A. Alzahrani, "An adaptable and personalized framework for top-N course recommendations in online learning," *Sci. Rep.*, vol. 14, no. 1, p. 10382, May 2024, doi: 10.1038/s41598-024-56497-1.

[22] P. V. Kulkarni, S. Rai, R. Sachdeo, and R. Kale, "Deep Learning-based Educational User Profile and User Rating Recommendation System for E-Learning," *J. Inf. Syst. Telecommun.*, vol. 11, no. 43, pp. 185–195, Aug. 2023, doi: 10.61186/jist.27448.11.43.185.

[23] Y. Ma, R. Ouyang, X. Long, Z. Gao, T. Lai, and C. Fan, "DORIS: Personalized course recommendation system based on deep learning," *PLoS One*, vol. 18, no. 6, p. e0284687, Jun. 2023, doi: 10.1371/journal.pone.0284687.

[24] I. Gunes, E. P. U. Gunes, and S. Aydın, "A Learning Material-Based Recommendation System For E-Learning," *Asian J. Distance Educ.*, vol. 18, no. 2, 2023, [Online]. Available: https://www.asianjde.com/ojs/index.php/AsianJDE/article/view/732

[25] C. Ju, J. Cao, Y. Yang, Z.-Q. Yang, and H. M. Lee, "Heterogeneity-aware Cross-school Electives Recommendation: a Hybrid Federated Approach," in *2023 IEEE International Conference on Data Mining Workshops (ICDMW)*, Dec. 2023, pp. 1500–1508. doi: 10.1109/ICDMW60847.2023.00191.

[26] Z. Xu, H. Lin, and M. Wu, "A Course Recommendation Algorithm for a Personalized Online Learning Platform for Students From the Perspective of Deep Learning," *Int. J. Inf. Technol. Web Eng.*, vol. 18, no. 1, pp. 1–17, Nov. 2023, doi: 10.4018/IJITWE.333603.

[27] S. Amin, M. I. Uddin, W. K. Mashwani, A. A. Alarood, A. A. O. Alzahrani, and A. A. O. Alzahrani, "Developing a Personalized E-Learning and MOOC Recommender System in IoT-Enabled Smart Education," *IEEE Access*, vol. 11, pp. 136437–136455, 2023, doi: 10.1109/ACCESS.2023.3336676.

[28] C. Troussas, A. Krouska, P. Tselenti, D. K. Kardaras, and S. Barbounaki, "Enhancing Personalized Educational Content Recommendation through Cosine Similarity-Based Knowledge Graphs and Contextual Signals," *Information*, vol. 14, no. 9, p. 505, Sep. 2023, doi: 10.3390/info14090505.

[29] S. Assami, N. Daoudi, and R. Ajhoun, "Implementation of a Machine Learning-Based MOOC Recommender System Using Learner Motivation Prediction," *Int. J. Eng. Pedagog.*, vol. 12, no. 5, pp. 68–85, Nov. 2022, doi: 10.3991/ijep.v12i5.30523.

[30] Y. Zheng, "Context-Aware Collaborative Filtering Using Context Similarity: An Empirical Comparison," *Information*, vol. 13, no. 1, p. 42, Jan. 2022, doi: 10.3390/info13010042.

[31] K. K. Jena *et al.*, "E-Learning Course Recommender System Using Collaborative Filtering Models," *Electronics*, vol. 12, no. 1, p. 157, Dec. 2022, doi: 10.3390/electronics12010157.

[32] G. S. Hukkeri and R. H. Goudar, "Machine Learning-Based Personalized Recommendation System for E-Learners," in *2022 Third International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*, Dec. 2022, pp. 1–6. doi: 10.1109/ICSTCEE56972.2022.10100069.

[33] R. P. Bijwe and A. B. Raut, "Comparative Analysis of Various Recommender Systems for Learners Using Artificial Intelligence," in *2024 First International Conference on Data, Computation and Communication (ICDCC)*, Nov. 2024, pp. 773–779. doi: 10.1109/ICDCC62744.2024.10960930.

[34] N. Vedavathi and R. Suhas Bharadwaj, "Deep Flamingo Search and Reinforcement Learning Based Recommendation System for E-Learning Platform using Social Media," *Procedia Comput. Sci.*, vol. 215, pp. 192–201, 2022, doi: 10.1016/j.procs.2022.12.022.

[35] T. Ahajjam, M. Moutaib, H. Aissa, M. Azrour, Y. Farhaoui, and M. Fattah, "Predicting Students' Final Performance Using Artificial Neural Networks," *Big Data Min. Anal.*, vol. 5, no. 4, pp. 294–301, Dec. 2022, doi: 10.26599/BDMA.2021.9020030.

[36] W. Kaiss, K. Mansouri, and F. Poirier, "Personalized e-learning recommender system based on a hybrid approach," in *2022 IEEE Global Engineering Education Conference (EDUCON)*, Mar. 2022, pp. 1621–1627. doi: 10.1109/EDUCON52537.2022.9766650.

[37] Q. Zhang, J. Lu, and G. Zhang, "Recommender Systems in E-learning," *J. Smart Environ. Green Comput.*, vol. 1, no. 2, pp. 76–89, May 2022, doi: 10.20517/jsegc.2020.06.

[38] M. Amane, K. Aissaoui, and M. Berrada, "A Multi-agent and Content-Based Course Recommender System for University E-learning Platforms," in *Digital Technologies and Applications*, 2021, pp. 663–672. doi: 10.1007/978-3-030-73882-2_60.

[39] L. Zhao and Z. Pan, "Research on Online Course Recommendation Model Based on Improved Collaborative Filtering Algorithm," in *2021 IEEE 6th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, Apr. 2021, pp. 437–440. doi: 10.1109/ICCCBDA51879.2021.9442575.

[40] Q. Li and J. Kim, "A Deep Learning-Based Course Recommender System for Sustainable Development in Education," *Appl. Sci.*, vol. 11, no. 19, p. 8993, Sep. 2021, doi: 10.3390/app11198993.

[41] G. Xu, G. Jia, L. Shi, and Z. Zhang, "Personalized Course Recommendation System Fusing with Knowledge Graph and Collaborative Filtering," *Comput. Intell. Neurosci.*, vol. 2021, no. 1, Jan. 2021, doi: 10.1155/2021/9590502.

[42] T. B. Lalitha and P. S. Sreeja, "Personalised Self-Directed Learning Recommendation System," *Procedia Comput. Sci.*, vol. 171, pp. 583–592, 2020, doi: 10.1016/j.procs.2020.04.063.

[43] P. B. Kikunda, J. Ndikumagenge, L. Ndayisaba, and T. Nsabimana, "Explainable Bayesian Network Recommender for Personalized University Program Selection," *J. Comput. Theor. Appl.*, vol. 3, no. 1, pp. 17–33, Jun. 2025, doi: 10.62411/jcta.12720.

[44] K. K. San, H. H. Win, and K. E. E. Chaw, "Enhancing Hybrid Course Recommendation with Weighted Voting Ensemble Learning," *J. Futur. Artif. Intell. Technol.*, vol. 1, no. 4, pp. 337–347, Jan. 2025, doi: 10.62411/faith.3048-3719-55.

[45] A. Ma, "Coursera Course Dataset 2023," *Kaggle*, 2023. https://www.kaggle.com/datasets/tianyimasf/coursera-course-dataset

[46] A. Papadimitriou, "Python's Contribution to Artificial Intelligence in Education: A state-of-the-art review," *J. Futur. Artif. Intell. Technol.*, vol. 2, no. 3, pp. 445–475, Oct. 2025, doi: 10.62411/faith.3048-3719-267.